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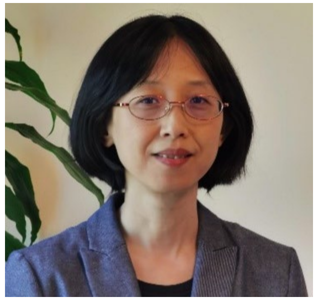
TRANSFORMING DEMENTIA CARE

Long-Term Care DATA COOPERATIVE

Bridging Research and Practice: An Update from Real World Data Scholars



Jinying Chen, PhD
Boston University Chobanian & Avedisian School of Medicine

Validating Medication Orders by Leveraging Natural Language Processing

Lindsay White, PhD
University of Pennsylvania Perelman School of Medicine

Determination of Cognitive Status in NH Residents: The Utility of EHR Data

Kenneth Lam, MD, MAS
University of Colorado School of Medicine

Validation of Functional Measures in LTC EHR Data

Yongkang Zhang, PhD, MS
Weill Cornell Medical College

Evaluating LTC Data Cooperative EHRs to Study T2D among Nursing Home Residents

Housekeeping

- All participants will be muted
- Enter **all questions** in the Zoom **Q&A/chat box** and send to Everyone
- Moderator will review questions from chat box and ask them at the end
- Visit impactcollaboratory.org
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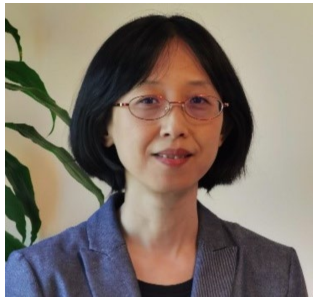
Validating Medication Orders by Leveraging Natural Language Processing

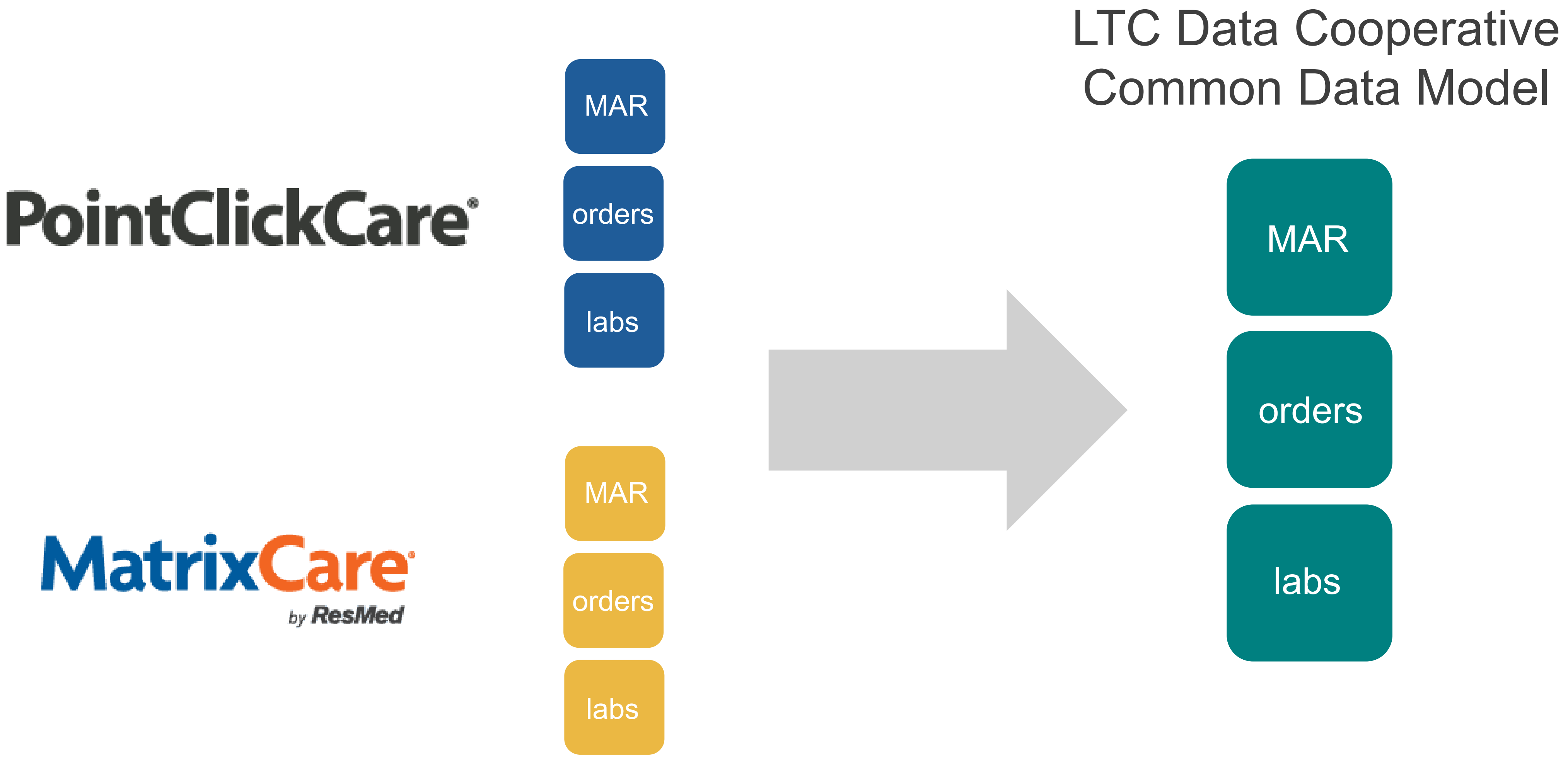


Jinying Chen, PhD

Assistant Professor

Boston University Chobanian & Avedisian School of Medicine

LTC Data Cooperative Dataset



Objective: Validate text fields for medication names

- Develop NLP-based methods to detect and correct medication name errors
- Create a validation set to measure the accuracy of NLP-based methods
- Assess the error rate in the medication_name field of the LTCDC dataset

NLP methods for error detection

- Create training/development/test sets from RxNorm drug names
  - Negative instances: RxNorm generic and branded drug names
  - Positive instances: drug names with automatically generated typos
- DrugBERT and charDrugBERT
  - finetuned Medical BERT and Medical Character BERT using training and development sets
- Spellchecker (baseline)
  - knowledge-based, dictionary extended with drug names from training and development sets

LTCDC data used for creating the validation set

Database	Ltcdc-20231215	Ltcdc-20240523
# of unique medication names	103,385	115,381
Freq <= 1	73082 (71%)	79023 (68%)
Freq <= 2	81520 (79%)	88507 (77%)
Freq <= 20	95113 (92%)	105760 (91%)
Freq <= 100	99132 (96%)	109813 (95%)

Validation set 1 derived from LTC medication names

- 2000 single-word medication names randomly chosen from the medication_name field of the ltcdc_20231215 database
  - 1500 : occurred 1 or 2 times in the database
  - 500 : occurred >1000 times in the database

- Using a semi-automatic method to identify errors from medication names
  - 1500 low-frequency names: reviewed in two rounds by the research team
  - 500 high-frequency names: verified using the Google search API spell check

Validation set 1 derived from 2000 LTC medication names

Data	N (%)	Examples	Note
Total	2000 (100)		
High frequency drug name (Correct)	500 (25)	Flexitol Cozaar Nizoral	Verified by Google search API spell checking
Correct drug name	569 (28.5)	Tranzarel Dacogen	Found on official websites
Correct short drug name	50 (2.5)	LIDO/ALUMINUM/SIMET glucosamine/chondr/msm	Found on official websites but not standard drug name
Misspelled drug name	742 (37.1)	levison -> levsin Ketocanozole -> Ketoconazole Ducolox -> Dulcolax	Used google search suggestion to find the correct drug name
Correct non-drug name	65 (3.3)	Starch Gentle	
Misspelled non-drug name	13 (0.7)	Adenovir -> adenovirus	
Not Sure	61 (3.1)	Wabana Dukes	Anything not in the other categories

Validation set 2 derived from LTC medication names

- 2000 medication names chosen from the medication_name field of the ltcdc_20240523 database using weighted random sampling

- Using a semi-automatic method to identify errors from medication names
  - low-frequency names (prescribed for <100 patients): reviewed in two rounds by the research team
  - high-frequency names (prescribed for at least 100 patients): verified using the Google search API spell check

NLP performance on error detection, using LTC validation sets 1 & 2

Metric	spellChecker (M1), mean (std)	charBERTDrug (M2), mean (std)	BERTDrug (M3), mean (std)
Precision	0.489 (0.006)	0.600 (0.008)	**0.605 (0.012)**
Recall	**0.961 (0.003)**	0.787 (0.019)	0.741 (0.025)
F1	0.648 (0.005)	**0.681 (0.007)**	0.666 (0.008)
Accuracy	0.570 (0.005)	**0.695 (0.005)**	0.693 (0.007)
Specificity	0.296 (0.006)	0.631 (0.015)	**0.659 (0.023)**
ROC AUC	0.628 (0.004)	0.749 (0.006)	**0.763 (0.006)**
PR AUC	0.486 (0.006)	0.606 (0.010)	**0.653 (0.010)**

Rule-based NLP for error detection in LTC workspace

- Using words from high frequency medication names (i.e., prescribed for 100 or more patients) to derive the dictionary used by NLP spellchecker

- Multiprocessing, using 2 processors

- 7 seconds to process 109790 medication names from ltcdc_20240523 that were prescribed to 1-99 patients

Error rate of LTCDC medication names, estimated by NLP vs. LTC validation set 2 (manual + google)

Medication Names	Total *N* (medication x person)	Estimated No. of errors (error rate)	
		NLP	LTC validation set 2
ordered or administered	36,931,407	217,173 (0.0059)	223,301 (0.0060)
ordered and administered	36,638,634	151,332 (0.0041)	154,691 (0.0042)
ordered	292,773	65,841 (0.2249)	75,447 (0.2577)

Rule-based NLP for error correction in LTC workspace

- Multiprocessing using 3 processors
- Using rules to exclude certain words (e.g., 200 mg, CVS) from the input of the NLP spellchecker
- 45 min – 1hr for processing and correcting 10000 medication names from ltcdc_20240523
- Processed 109790 medication names (prescribed to 1-99 patients) in ~11hr

Collaboration

PI/Scholar :

Jinying Chen, PhD,

Boston University Chobanian & Avedisian School of Medicine

Co-investigators/Mentors:

Andrew Zullo, PharmD, PhD, School of Public Health, Brown University

Kevin McConeghy, PharmD, School of Public Health, Brown University

Acknowledgements

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Validation of Functional Measures in LTC Electronic Health Record (EHR) Data

Kenneth Lam, MD, MAS

Geriatrician, Assistant Professor

University of Colorado
School of Medicine

Objectives

- Determine the type and frequency of functional assessments in the LTC Data Cooperative
- Provide a brief overview of how functional assessments in the Minimum Data Set 3.0 have evolved since 2010
- Evaluate methods for cross-walking new Section GG measures in the MDS 3.0 to old Section G measures

An overview of assessment types

Assessment types	Short for…	Measure of	Count (in 10^3)
MDS3	Minimum Data Set 3.0	Comprehensive	6,683
ADL	Activity of Daily Living	Function	2,821
FS	Function Score	Function	2,100
CPS	Cognitive Performance Scale	Cognition / Function	2,100
CAM	Confusion Assessment Method	Delirium	2,100
BIMS	Brief Inventory of Mental Status	Cognition	1,737
PHQ-9	Patient Health Questionnaire	Depression	1,607
PHQ-9-OV	Patient Health Questionnaire	Depression (observed)	188

Data from 02/2024

The ADL and FS assessments are (mostly) derived from the MDS

- The ADL assessment comes from the Care Assessment Area (CAA), where SNFs should respond to identified problems with ADLs
- The FS assessment (from 0-16) likely refers to the RUG-IV ADL score, which is derived from functional measures in the MDS for bathing, transfers, eating, and toileting
- >99% assessments co-occur (share a date) with an MDS

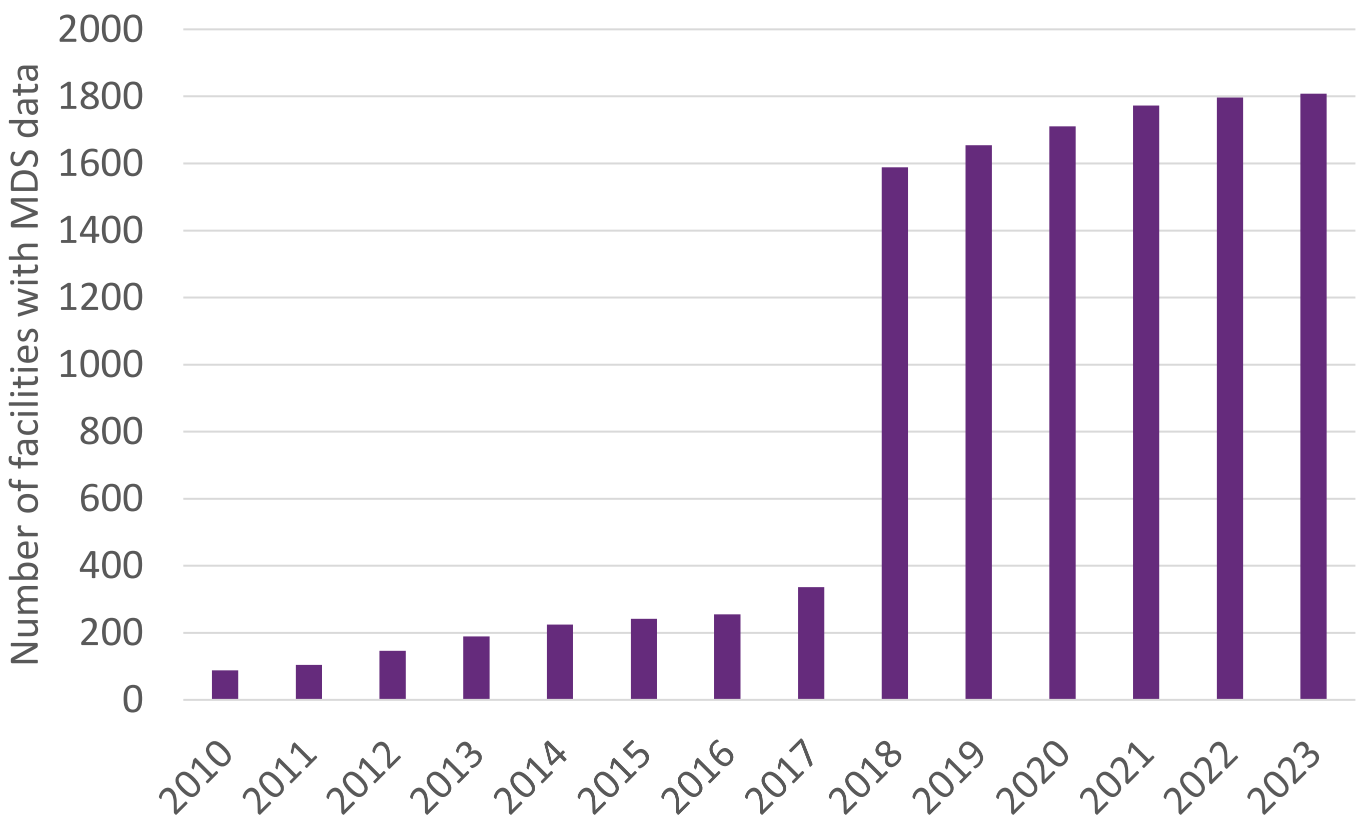
Functional measures within the MDS have changed over time

Year	MDS Version	Section G	Section GG	Major change
Pre 2010	2.0	✓		Original Section G from which the MDS-ADL (1999) was created
2010	3.0 V1.04	✓		MDS 2.0 to MDS 3.0 (to improve clinical relevance, accuracy, validity, more resident voice)
2016	3.0 V1.14	✓	✓	Added Section GG for SNF PPS (prospective payment system for rehab, admission vs. discharge performance & goals for: eating, oral hygiene, toileting, sit to lying, lying to sitting, sit to stand, chair transfer, toilet transfer, 50ft, 50ft & 2 turns, 150ft)
2017	3.0 V1.15	✓	✓	
2018	3.0 V1.16	✓	✓	Added prior function (self-care, mobility, stairs, cognition) and device use, added activities (shower/bathing, upper dressing, lower dressing, footwear, roll left and right, car transfer, 10ft uneven, 1 step, 4 steps, 12 steps, picking up objects)
2019	3.0 V1.17	✓	✓	Added interim performance for status updates
2023	3.0 V1.18		✓	Section GG only, including for SNF OBRA assessments, added activities on admission/discharge (personal hygiene, tub/shower transfer)
2024	3.0 V1.19		✓	Functional limitation in ROM

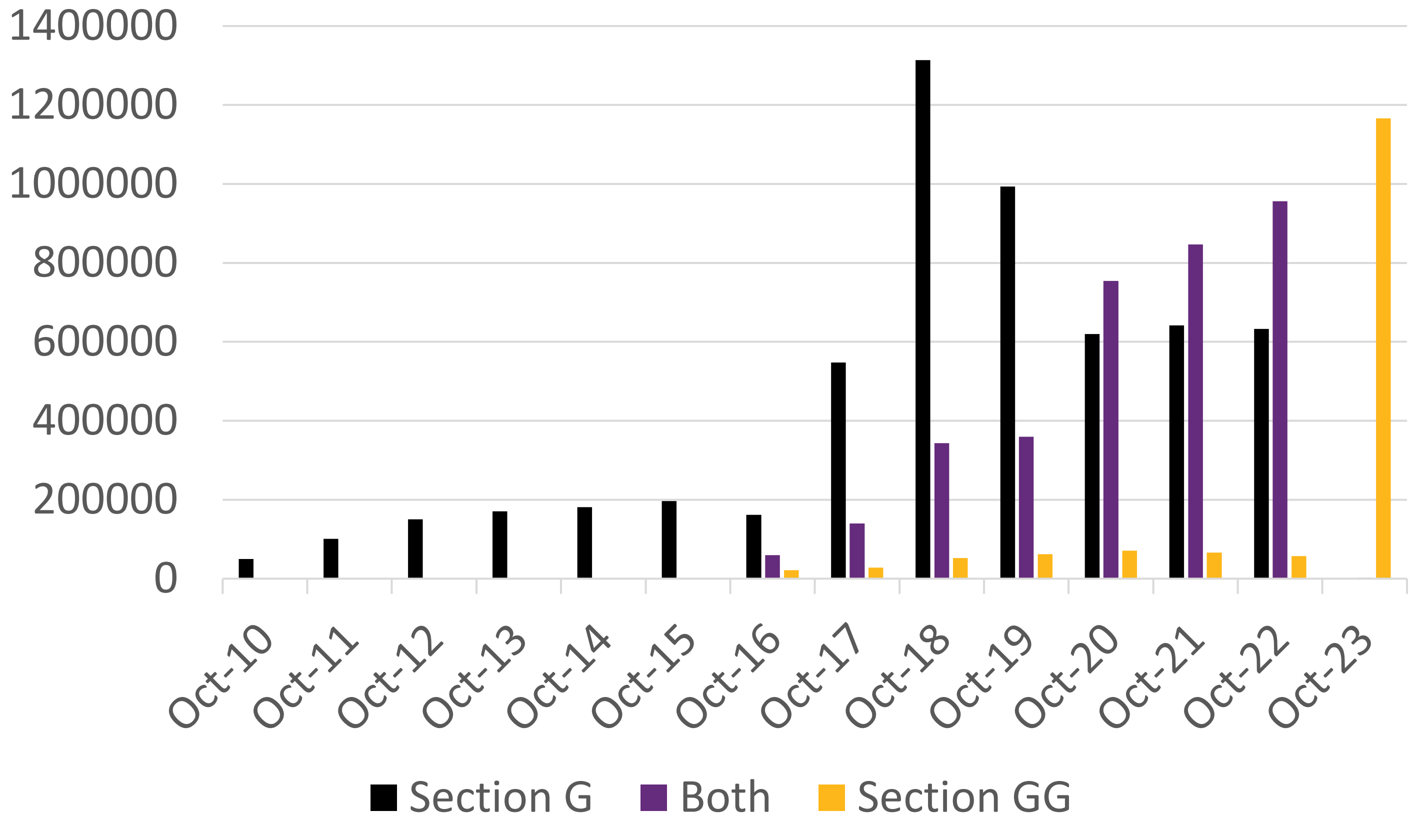
Changing measures present challenges for research

- New scale (Section GG) as of October 2023
- Changing items within that scale as it was being implemented
- Changing indications for when that scale should be completed
- Cannot construct longitudinal cohorts / longitudinal outcomes
- Unclear how to interpret Section GG compared to previous Section G scores
- Risk of instability over time as function is linked to payment

Over time, more facilities have joined the LTC Data Cooperative



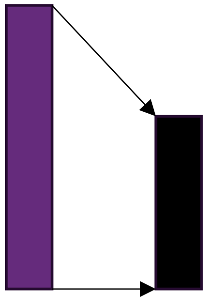
We thus have many Section G and Section GG measurements during the implementation period



Can we use assessments conducted on the same people at the same time to cross-walk scores?

Comparing four methods to cross-walk scores

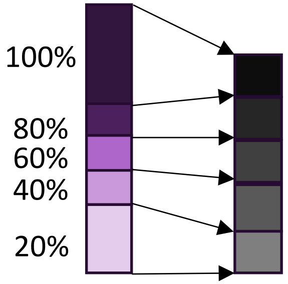
1. Scaled summary score



2. Item-based coding

Section GG		Section G
GG0170C	→	G0110A
GG0170E	→	G0110B
GG0130A	→	G0110H1
GG0130C	→	G0110I1

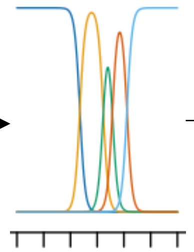
3. Equipercentile method



4. Item response theory-based methods

Section GG
GG0170C
GG0170E
GG0130A
GG0130C

→

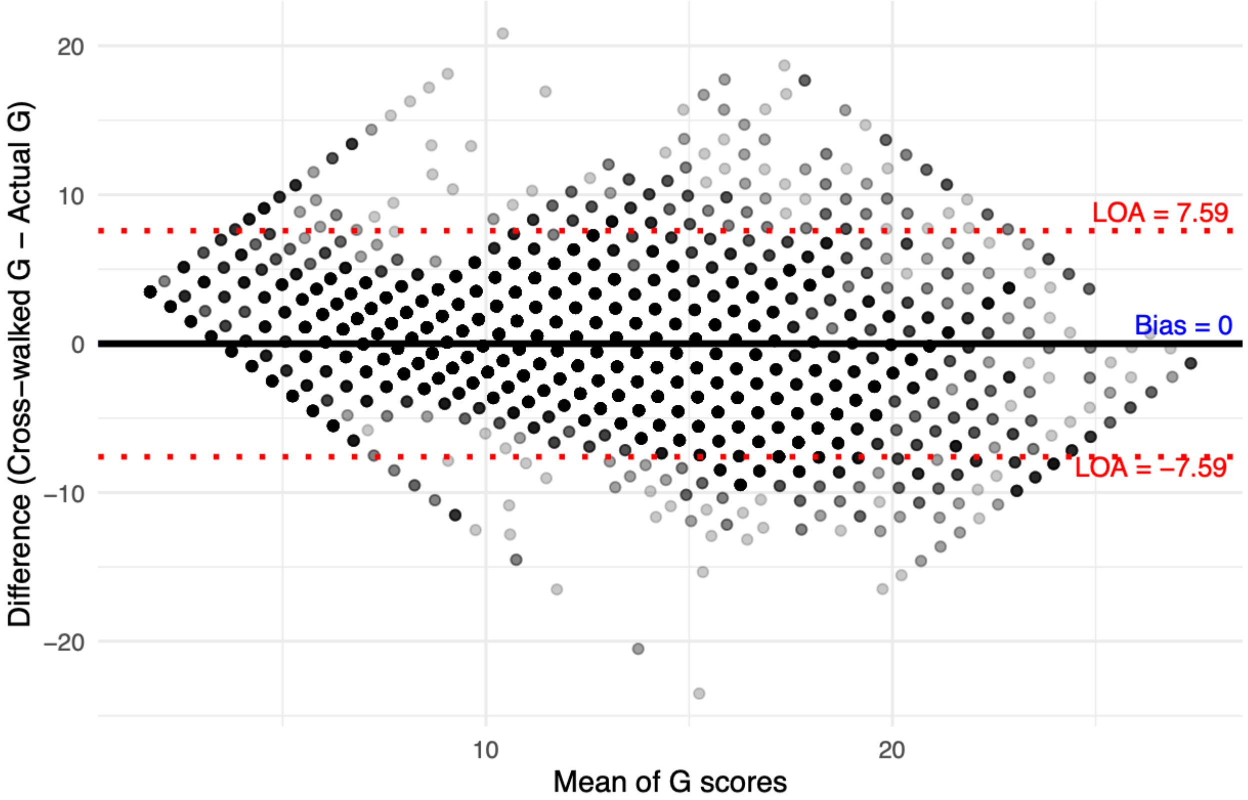


→

Section G
G0110A
G0110B
G0110H1
G0110I1

How do we visualize how well each method works?

- Bland-Altman plots show the difference between the cross-walked & actual score vs. the mean of the scores
- Bias = mean difference
- LOA = level of agreement; 95% of the time, the cross-walk produces a difference less than this range



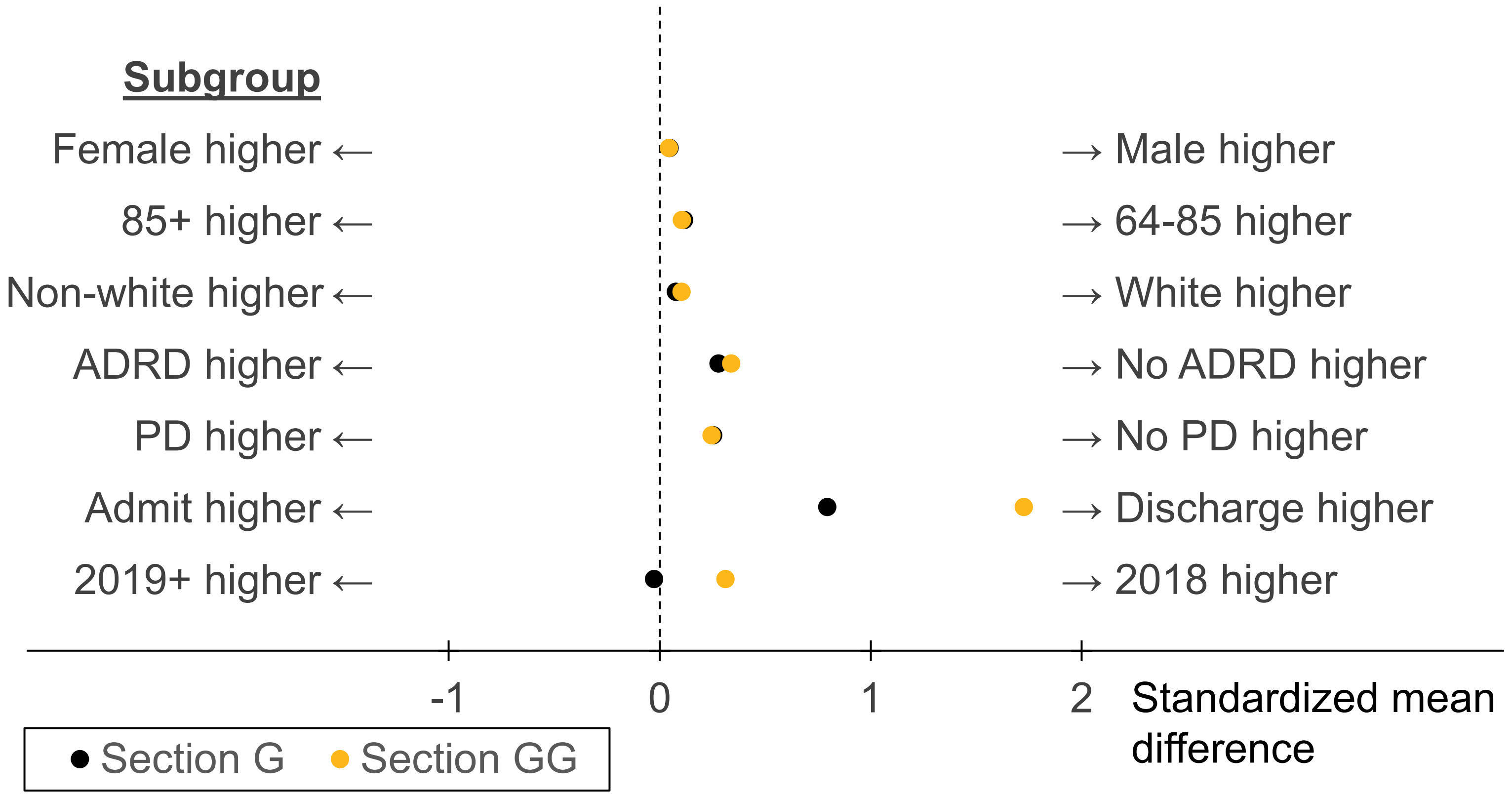
Overall comparison of methods

Method	Spearman correlation	Bias	Level of agreement
Scaled summary score	0.704	-3.50	8.08
Item-based coding	0.692	+0.06	7.77
Equipercentile	0.700	-0.03	8.13
Item response theory (Stocking-Lord)	0.694	0.00	7.59

So it really is not easy to reliably cross-walk Section GG to Section G

- Tests of fit (confirmatory factor analyses, exploratory factor analyses) do not clearly indicate that Section GG items and Section G items measure the same thing
- The overall Section GG score produces greater differences than Section G when it should not

Section GG differs more for discharge assessments and after PDPM



Next steps…

- Explore why Section GG does not cross-walk well to Section G (exploratory factor analyses, factor loadings, differential item functioning)
- Publish guidance on how to handle longitudinal Section GG functional measures for research as an outcome measure for comparative effectiveness research
  - Will especially need an approach as quality-based payments for discharge function score are being implemented, which may further introduce problems for validity
- For future studies, should we abandon a single scale for function?

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Determination of Cognitive Status in Nursing Home (NH) Residents: The Utility of Electronic Health Record (EHR) Data

Lindsay White, PhD, MPH

Senior Research Investigator

University of Pennsylvania

Perelman School of Medicine

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  - Elizabeth White, PhD, APRN
  - Cyrus Kosar, PhD, MA

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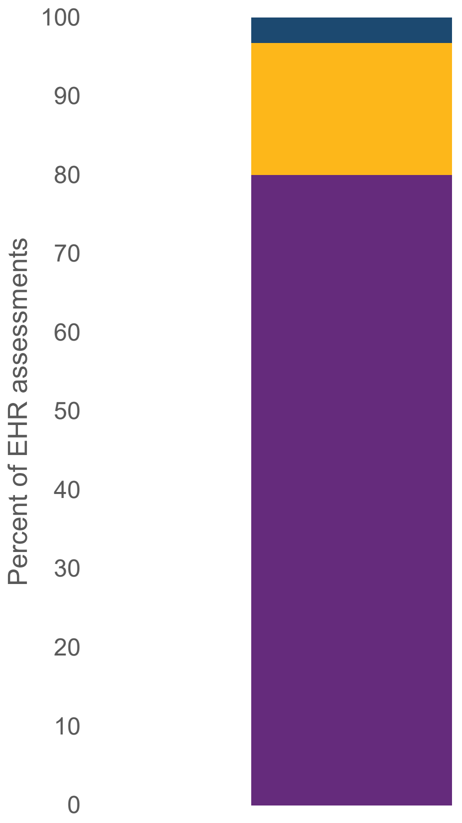
Background and objectives

- Accurate assessment of cognitive functioning in nursing home residents is crucial for:
  - Appropriate care planning
  - Monitoring of quality of care
  - Identifying populations of interest for research purposes

- Objective: To examine whether and under what circumstances EHR data on nursing home residents provides useful cognitive status information above and beyond what is available through the MDS
  - Describe the EHR cognitive assessment data across time, facilities, and resident populations
  - Examine the validity of the EHR cognitive assessment data
  - Examine within resident variation in cognitive functioning over time

Cognitive assessment validation findings

Types of cognitive assessments in the EHR data: BIMS, CPS, and CAM



3.2% occur outside of the reference period → Only BIMS are usable

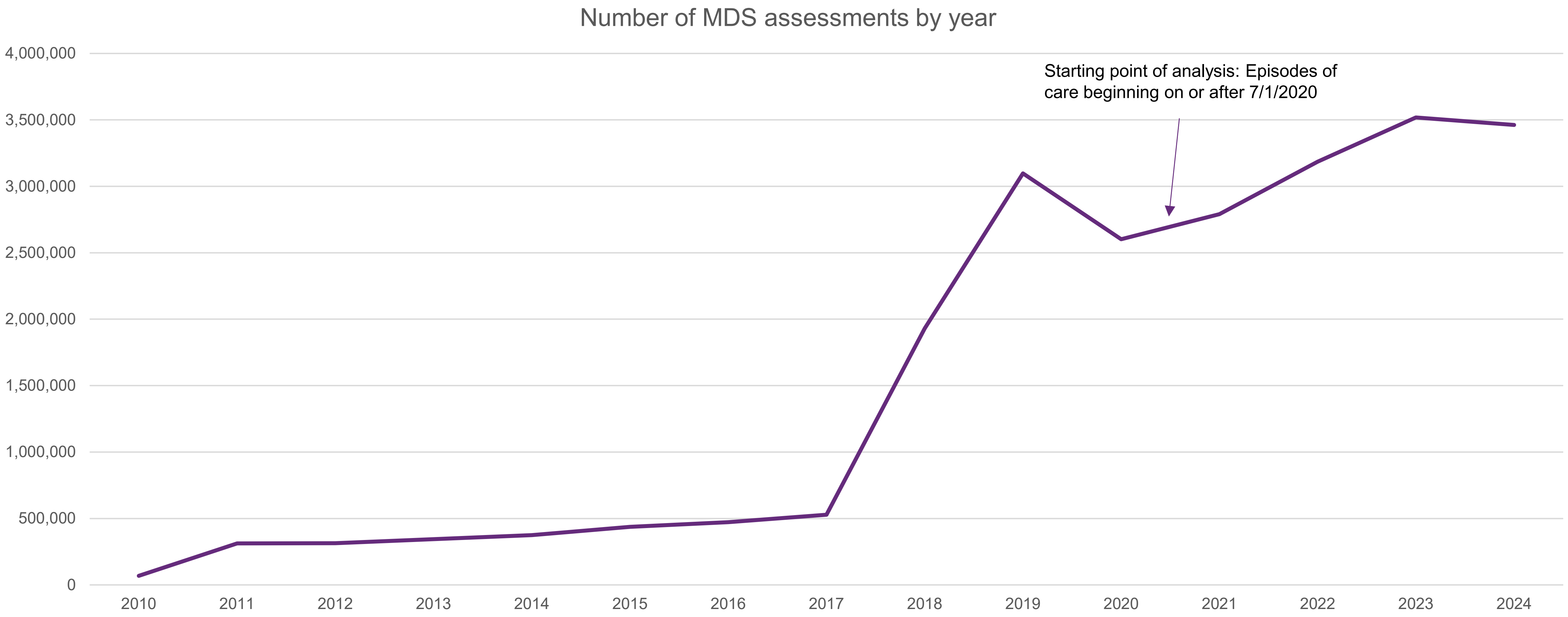
16.7% occur on a different day, but within the reference period of an MDS assessment → ~90% agreement on score, but CAM assessments in EHR systematically miss delirium captured in the MDS

80.1% of cognitive assessments in the EHR data occur on the same day as an MDS assessment → ~99% agreement on score, but CAM assessments in EHR systematically miss delirium captured in the MDS

Pivot to new objectives

- Delirium is understudied in the nursing home setting
- Extant literature
  - Dated
  - Based on small, non-generalizable samples
  - Focuses on newly admitted post-acute care patients
- Objectives:
  - Describe CAM data among short and long stay residents
  - Determine prevalence of delirium among short and long stay residents
  - Explore clinical correlates of incident delirium within each population

MDS assessments in the EHR data



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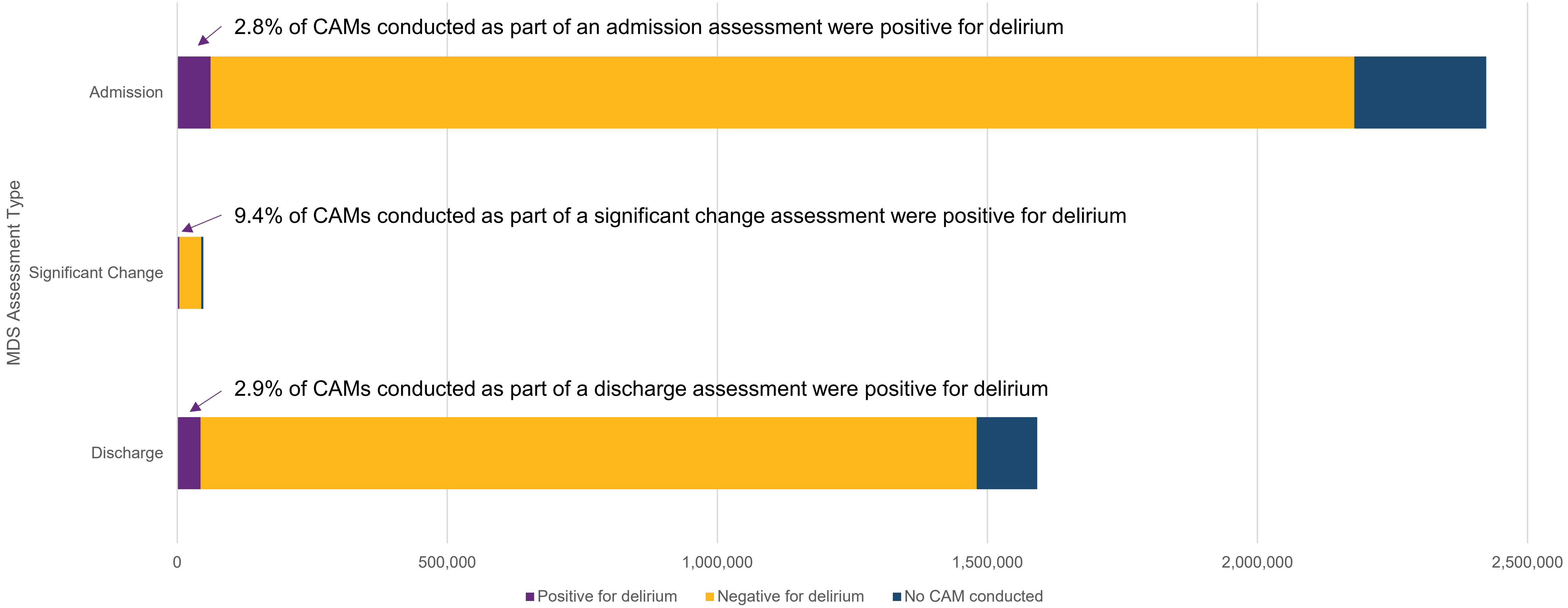
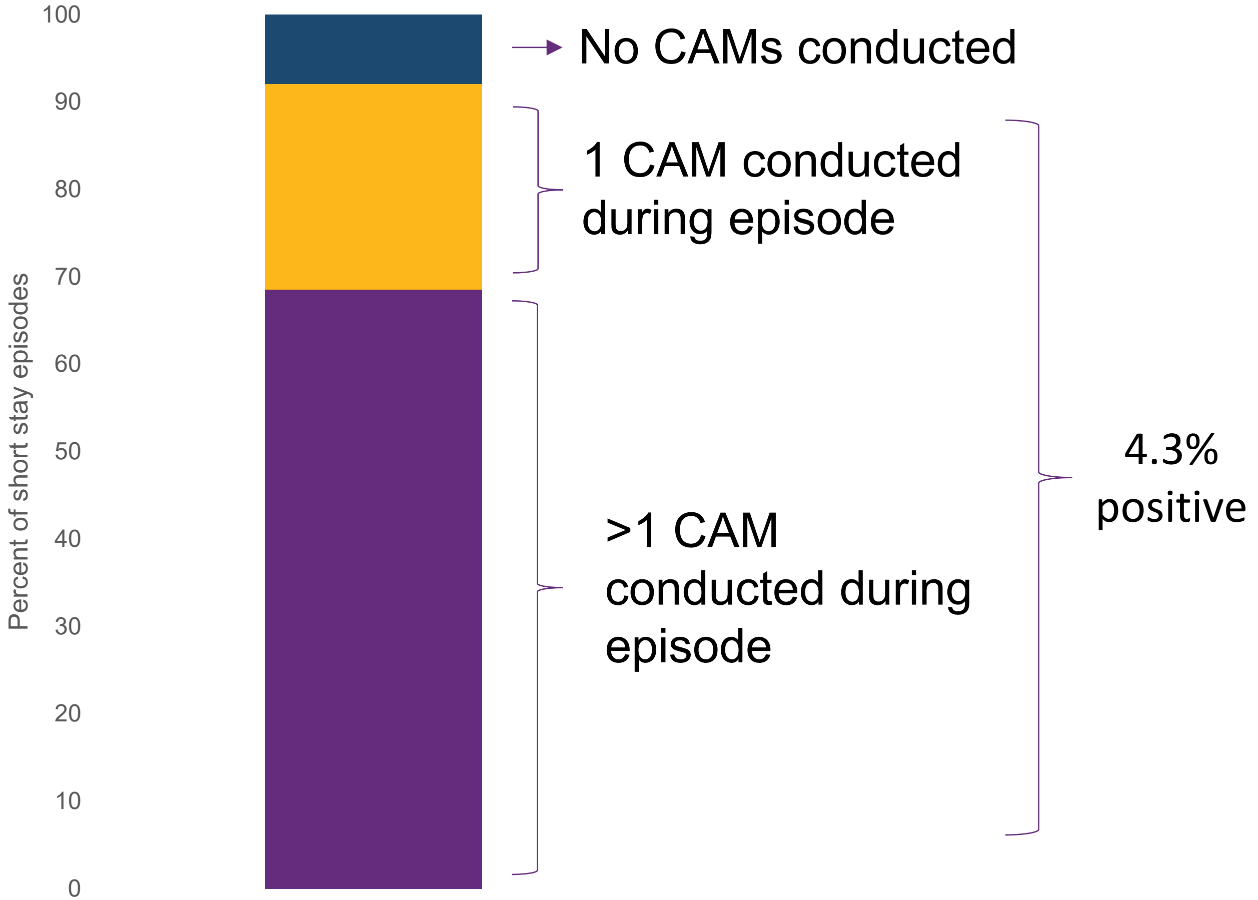
Short stay episode assessments



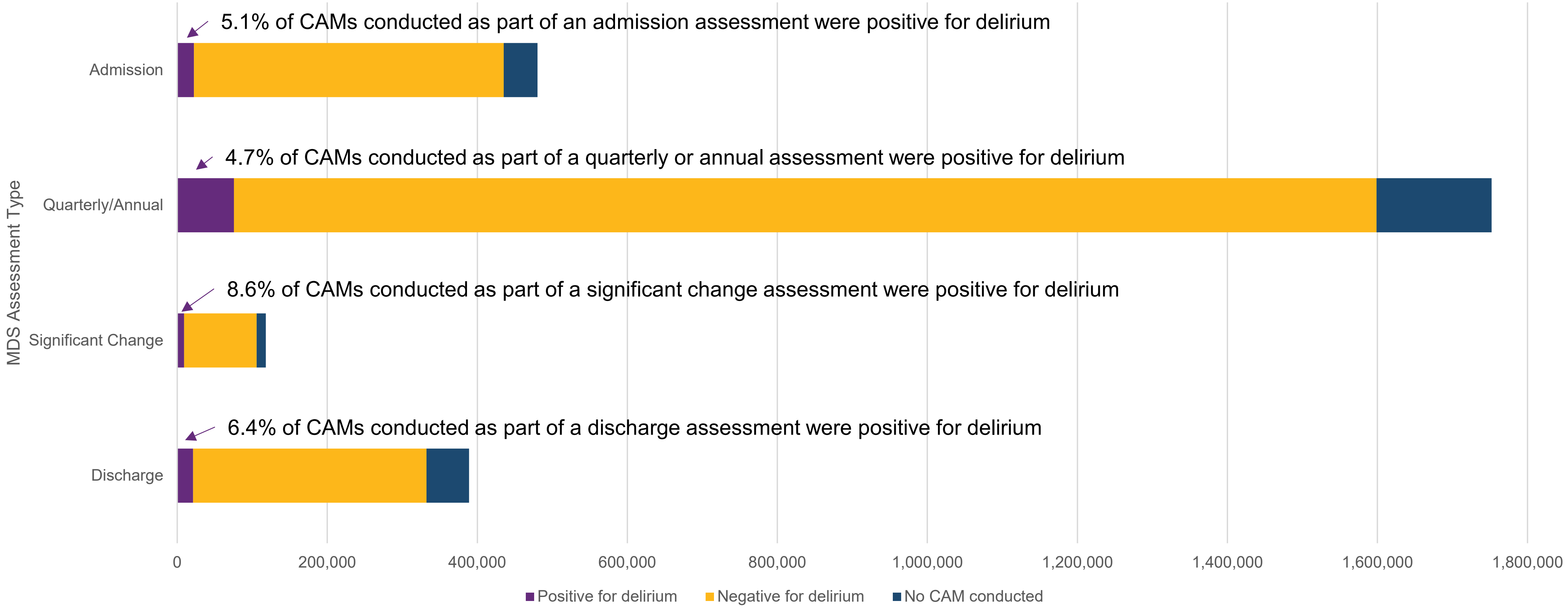
Short stay episodes



Discharge disposition

	Delirium	No delirium
Home	30.8%	55.0%
Another facility	41.5%	26.3%
Hospice	1.6%	0.8%
Died	11.6%	4.6%
Unknown	14.5%	13.3%

Long stay episode assessments



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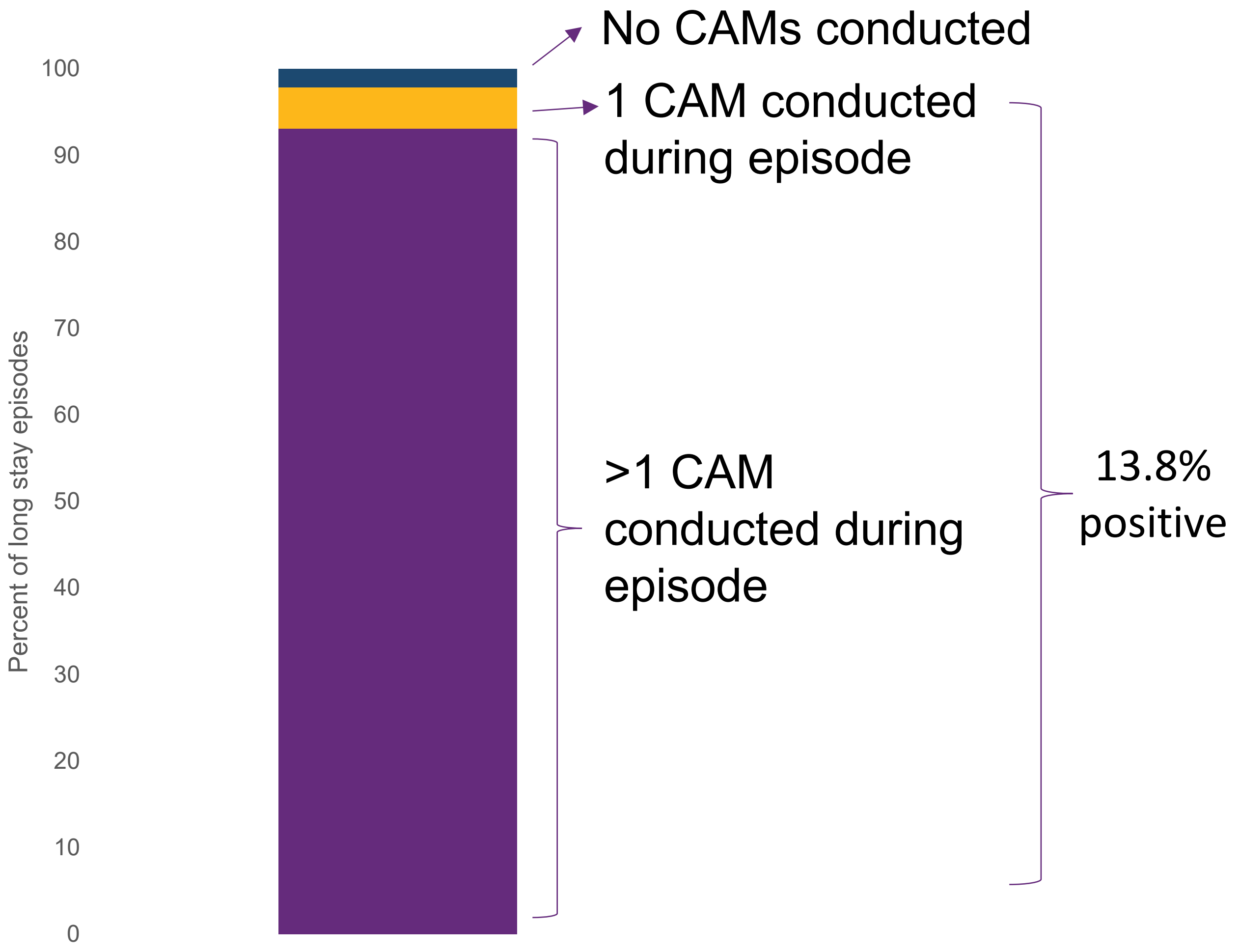
Long stay episodes



Trajectories	
10.1%	Positive for all CAM assessments
18.3%	Positive at first CAM assessment, but is not present in later assessments
52.1%	Negative at first CAM assessment, but positive in one or more subsequent assessments (“incident”) Timing of first positive relative to admission (days) median (IQR) – 190 (97-410)
19.5%	At least two separate instances of delirium, with resolution of delirium in between (“fluctuating”)

Long stay episodes

- For residents with “incident” or “fluctuating” delirium, 8.3% of delirium positive assessments were preceded by a hospitalization
- Mortality
  - Ever:
    - Long stay episodes where delirium was detected – 21.5%
    - Long stay episodes where delirium was not detected – 13.3%
  - Within 1 year of admission:
    - Long stay episodes where delirium was detected within the first year – 13.5%
    - Long stay episodes where delirium was not detected within the first year – 8.4%

Next steps

- Stratify by dementia status
- For long stay episodes, examine medications initiated within the 2 weeks prior to incident delirium

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Evaluating LTC Data Cooperative Electronic Health Record (EHR) to Study T2D among Nursing Home Residents

Yongkang Zhang, PhD, MS

Assistant Professor

Weill Cornell Medical College

Why Diabetes?

- Approximately 25-34% of nursing home residents have diabetes (Munshi et al., 2016).

- Diabetes is associated with significant disease burden and higher cost.
  - Diabetes-attributable nursing home costs were $9.6 billion and total nursing home costs of diabetic patients were $30 billion in 2022 (Parker, et al., 2024).

Why Diabetes?

- Challenges of diabetes management in nursing homes (Pandya et al., 2020; Idrees et al., 2022).
  - Extensive and heterogenous comorbidities
  - ADL dependence
  - Inadequate diabetes education for staff
  - High risk for severe hypo- and hyperglycemia
  - Variation in practices
- Data limitations have been a significant barrier for studying diabetes management in nursing homes
  - MDS file has limited information about diabetes.

Objective

- Identify data elements relevant to type 2 diabetes (T2D) in LTC Data Cooperative EHR.
- Assess quality and consistency between different data elements.
- Assess consistency between information from EHR and MDS.
- Compare the results to other similar studies focusing on T2D in nursing homes.

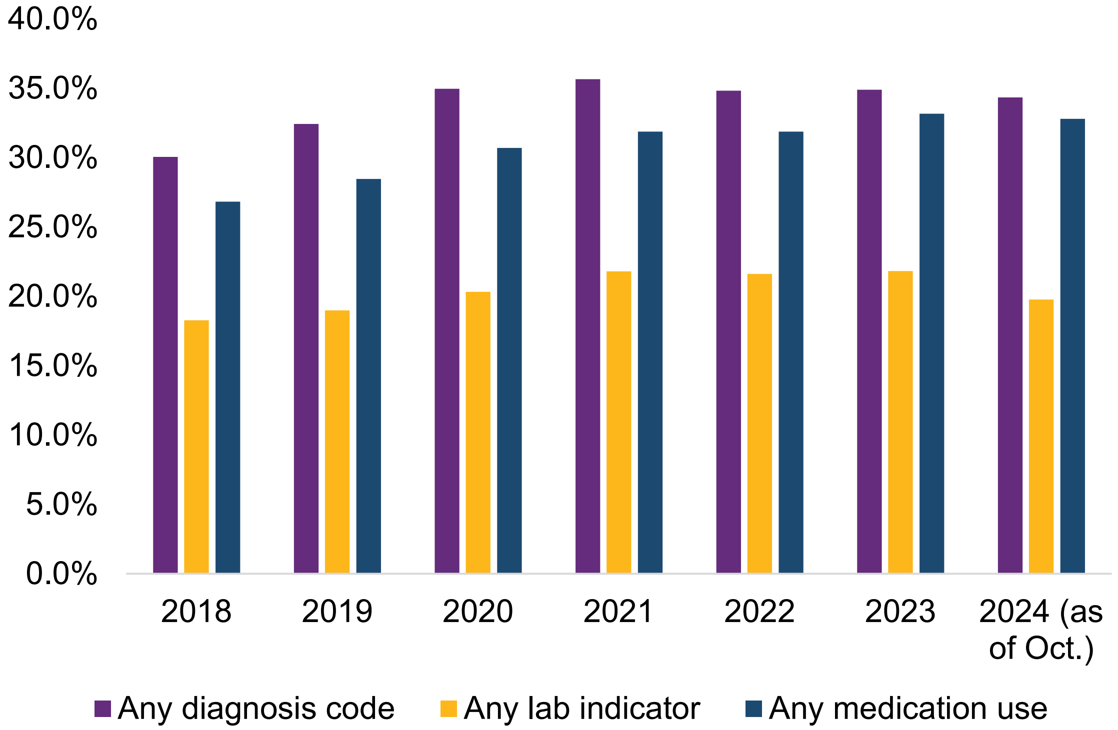
Key Findings: T2D Data and Availability

- Various data elements relevant to T2D are in different data tables.

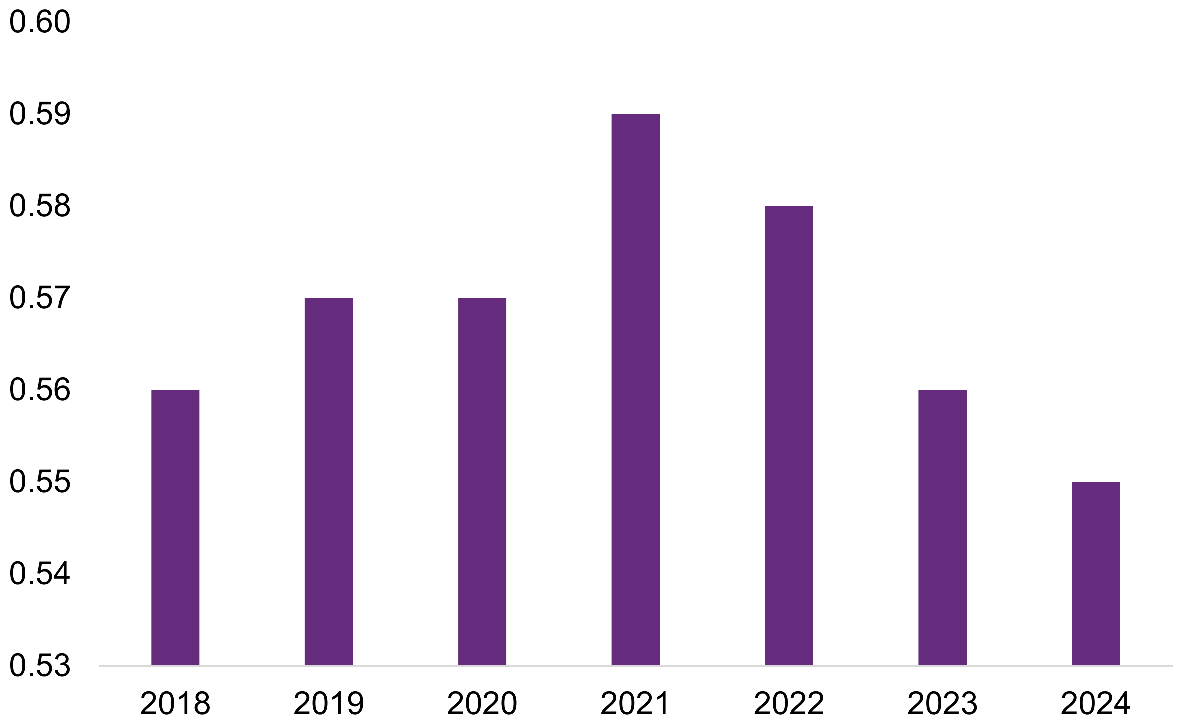
Data Tables	Data Elements	Availability
Condition	ICD-9/10 diagnosis codes; Diagnosis descriptions	Very well populated.
Episode	ICD-9/10 diagnosis codes (both admission and discharge diagnoses); Diagnosis descriptions	Very well populated; use both admission and discharge diagnosis codes.
Medication Administration	Medication generic name; Medication name	Medication name column has both generic and brand names. Need to account for spelling idiosyncrasies.
Medication Order	NDC; Medication generic name; Medication name; Medication class code description	NDC is not well available. Medication name column has both generic and brand names. Need to account for spelling idiosyncrasies.
Observation Lab	LOINC; Observation event code description; Observation result name	Very well populated. Need to be cautious about results and the unit of results.
MDS	I2900: Active Diagnoses: Diabetes Mellitus (DM) Code N0350A: Number of Days Insulin Injections	Very well populated

Key Findings: Agreement between EHR Elements

- % of residents with T2D identified by different EHR elements.

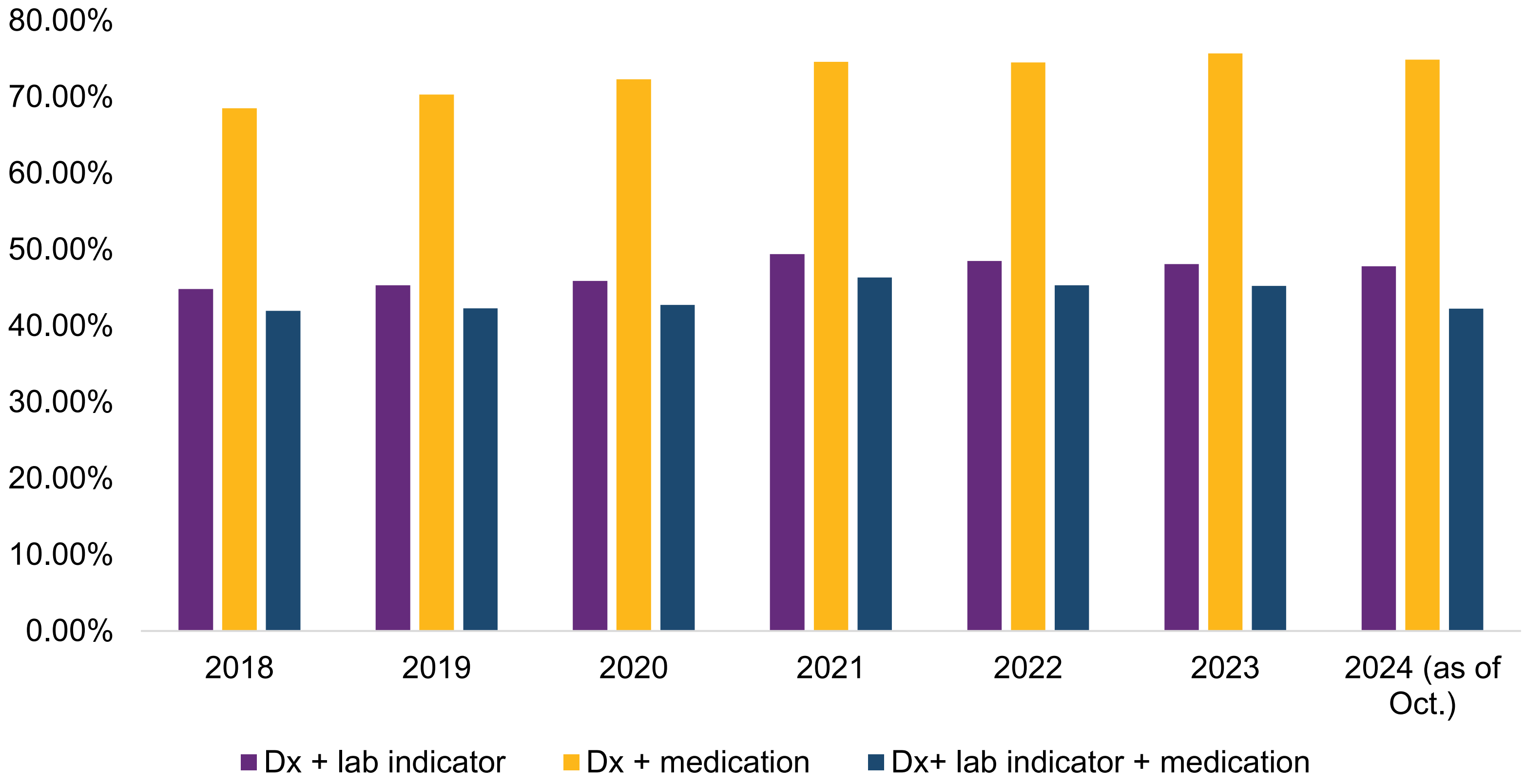


- Moderate agreement between EHR elements (Fleiss's Kappa).



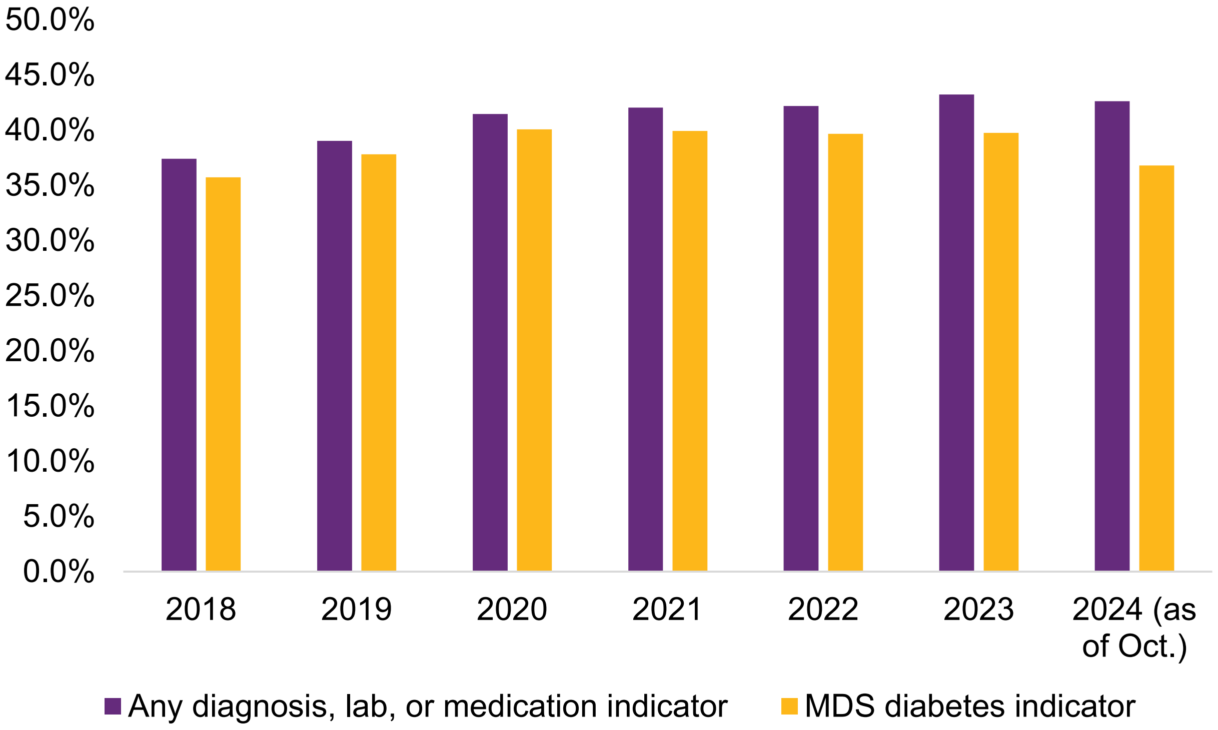
Key Findings: Agreement between EHR Elements

- Among all residents with a T2D dx, % with ≥ 1 lab indicator, ≥1 medication, or both

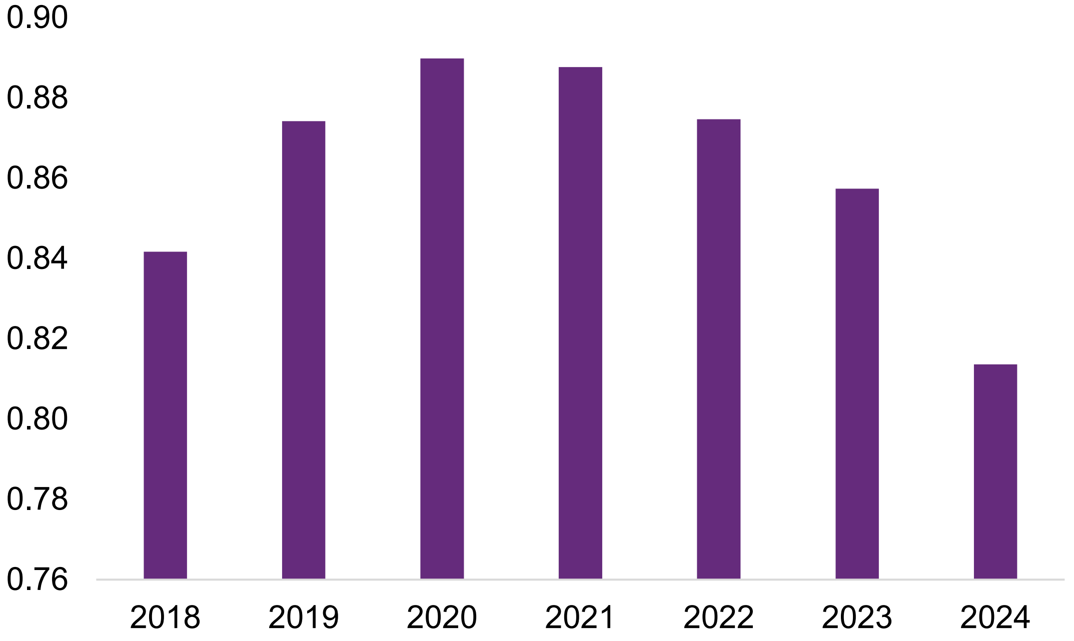


Key Findings: Agreement between EHR and MDS

- % of residents with T2D identified by EHR versus MDS.

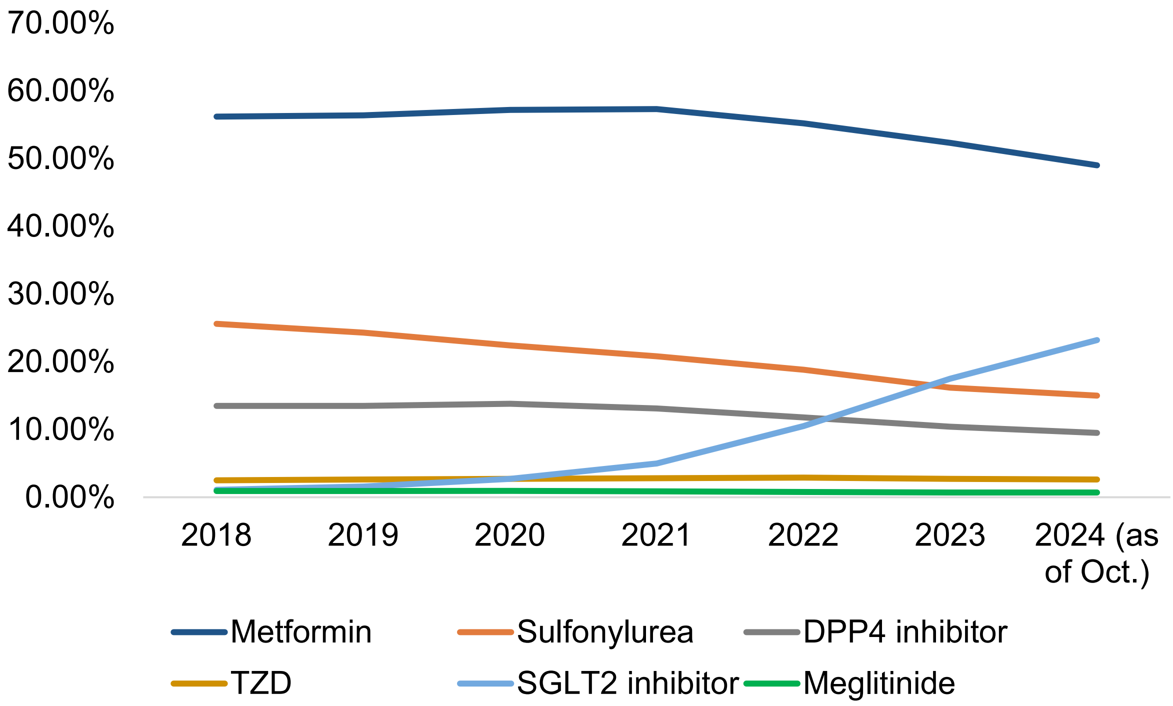


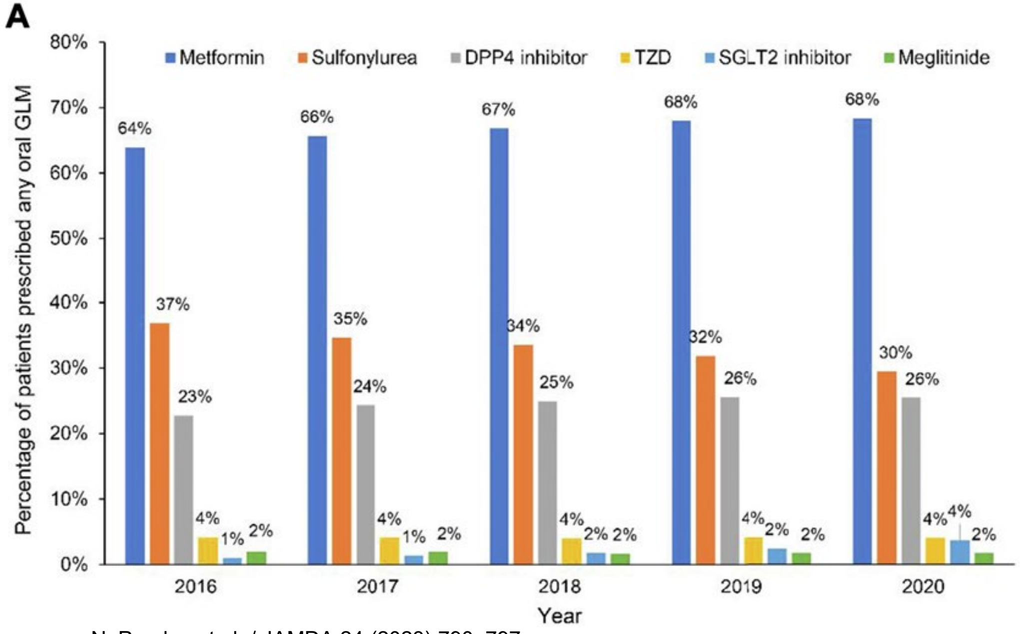
- Great agreement between EHR elements and MDS (Cohen's Kappa).



Key Findings: Use of Medication

- Among residents with T2D who were prescribed any oral glucose-lowering medication, metformin has been the most common one and SGLT2 inhibitor use has been growing. Patterns are consistent with a prior study.

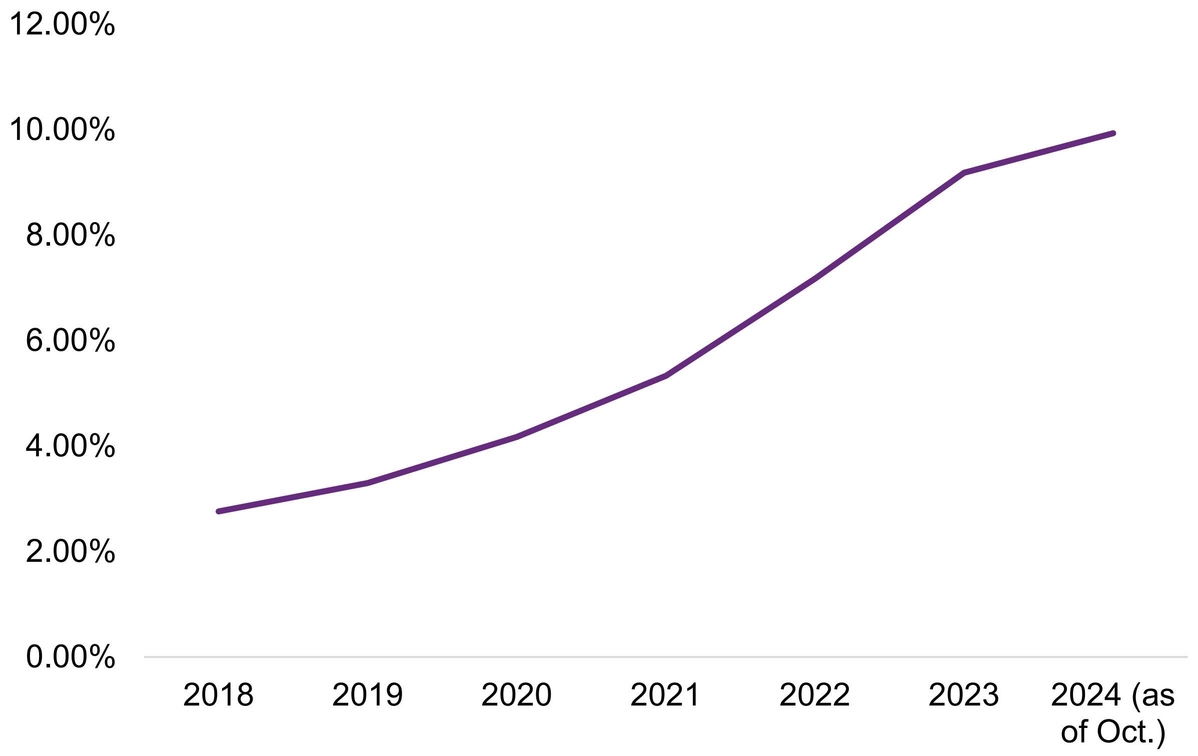




N. Pandya et al. / JAMDA 24 (2023) 790e797

Key Findings: Use of Medication

- Among residents with T2D who were prescribed any injectable glucose-lowering medication, the use of GLP-1 RA has been growing.



Acknowledgment

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- Mentors: Drs. Kaley Hayes and Daniel Harris
- Other RWD scholars

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